DSCI-6004-03 NATURAL LANGUAGE PROCESSING

PROJECT

ON

NEWS CATEGORY CLASSIFICATION USING NLP

BY

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Abstract

This project, "News Category Classification Using Natural Language Processing (NLP)," employs a diverse set of advanced models, including Long Short-Term Memory (LSTM), BERT, Distilled BERT, and RoBERTa, to automatically categorize news articles into predefined topics. The methodology encompasses the collection of a varied dataset, preprocessing techniques, and the exploration of NLP embeddings for feature extraction, with a focus on leveraging the strengths of each model. LSTM, known for its sequential data processing capabilities, and transformer-based models like BERT, Distilled BERT, and RoBERTa, renowned for capturing complex contextual information, contribute to the robustness of the classification system. Evaluation metrics such as accuracy, precision, recall, and F1 score are employed to assess the performance of these models. The project not only addresses the contemporary challenge of information overload but also showcases the versatility of different NLP architectures in enhancing news categorization accuracy and efficiency.

Introduction

In an era characterized by an overwhelming deluge of information, effective management and categorization of news articles have become imperative. The project, "News Category Classification Using Natural Language Processing (NLP)," delves into the application of cutting-edge NLP models to automate the classification of news content into predefined categories. By harnessing the capabilities of models such as Long Short-Term Memory (LSTM), BERT, Distilled BERT, and RoBERTa, the project aims to decipher the intricate nuances of textual data, enabling accurate topic identification. The investigation encompasses a diverse dataset, preprocessing techniques, and the utilization of NLP embeddings to extract meaningful features. The significance of this endeavor lies not only in addressing the challenges posed by information overload but also in showcasing the adaptability and effectiveness of various NLP architectures in optimizing news categorization accuracy and efficiency. As news consumption evolves, this project stands at the forefront of leveraging advanced technologies to streamline and enhance the categorization process, ultimately contributing to a more efficient and user-centric information landscape.

Data

The Huffpost dataset spans over a decade's worth of articles, from 2012 up until 2022, totaling 210,294 individual records. Each entry within this substantial catalog of online reporting contains identifying attributes offering insights into the nature of that particular post. A few of the salient data fields provide information such as the overarching category that article is classified under, the eye-catching headline created to draw readers' attention, the specific author or authors credited with reporting the piece, a URL link to access the full published version on Huffpost's website, a short 2-3 sentence synopsis giving a condensed summary, and the calendar date displaying when it originally appeared on the site.

Category - This field indicates the overall topic or subject that the article covers. Common Huffpost categories may include politics, entertainment, technology, wellness, parents, etc. Understanding the categories represented in the data can reveal insights into Huffpost's news priorities and coverage areas.

Headline - The headline contains the main title of the article, which serves to draw readers in and succinctly communicate the crux of the story and entice clicks. Analyzing the wording used in headlines over time could showcase how Huffpost aims to maximize engagement.

Authors - This attribute credits the individual writer(s), likely Huffpost staff or occasional contributors, who researched and authored the published story. Examining common author names could identify key journalists and influencers at the outlet.

Link - Every post features a URL linking directly to the full piece on Huffpost's website, which enables convenient access and referral to the publisher's platform and content library.

Short_description - A brief 2–3-line paragraph summarizes each article's main topic and focus to give readers more context without necessitating a full click-through. Evaluating these descriptions could reveal popular subjects.

Date - The date provides the exact calendar date when Huffpost published the article in question. Date trends may point to meaningful news events, zeitgeists, and shifts in public attention over the 2010s and 2020s.


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Methodology

Techniques/Models Used:

We experimented with various deep learning architectures including standard LSTM, bi-directional LSTM (Bi-LSTM), stacked LSTM, stacked Bi-LSTM and Transformer-based models like BERT, DistilBERT and RoBERTa to perform text classification. The sequential LSTM and Bi-LSTM models were chosen as baseline networks to capture temporal context and dependencies in the text data. The stacked variants offered additional depth for more complex feature learning. The pretrained language models like BERT leverage their contextual word embeddings and self-attention to achieve superior text understanding. RoBERTa was selected as the best performer after comparative evaluation.

- Simple LSTM We implemented a basic long short term memory (LSTM) recurrent neural network (RNN) for sequence modeling of text data. The model had an input layer to accept preprocessed tokenized text, an embedding layer to encode the tokens as dense vectors, a single LSTM layer with 128 units to learn temporal relationships, a 25% dropout layer for regularization and a output dense layer with sigmoid activation to perform multi-label text classification into 10 categories.
- Bidirectional LSTM We augmented the standard LSTM with a bidirectional LSTM (Bi-LSTM) where two LSTMs process the data in forward and backward sequence directions. This captures past and future context for improved text understanding. Our Bi-LSTM model configuration mirrored the simple LSTM but with 64 units in both directions, leading to 128 total units.
- Stacked LSTM For a deeper feature representation, we utilized stacking of multiple LSTM layers in sequence. Our stacked variant contains an embedding input followed by 2 LSTM layers with 256 units per layer and 0.2 dropout between layers before the output classification layer.
- Stacked Bi-LSTM Similarly, the stacked Bi-LSTM was constructed by having 2 Bi-LSTM layers, with the second layer receiving feature outputs from the first bidirectional layer as input. Each Bi-LSTM layer had 128 units.
- BERT We leveraged Google's Bidirectional Encoder Representations from Transformers (BERT) architecture, which is pretrained on massive text corpus using masked language modeling and next sentence prediction to create deep bidirectional representations. We initialized a base BERT model and added a classification layer on top to predict text categories based on BERT's contextual embeddings.
- Distilled BERT As BERT's scale leads to high compute costs, we evaluated DistilBERT - a distilled, smaller version of BERT that retains 97% language understanding capability with 40% fewer parameters. Our DistilBERT classifier was identical to BERT but utilized this compressed model as the text encoder backend.
- RoBERTa Facebook AI's Robustly Optimized BERT Approach (RoBERTa) enhances BERT pretraining through dynamic masking, full sentence inputs, and massive data resources. We found RoBERTa achieved strongest textual inference, allowing accurate classification with the fewest errors. Our RoBERTa architecture mirrors the BERT and DistilBERT, initialized from the robust pretrained checkpoints.

While our LSTM stacks modeled sequence data well, BERT-based transformers truly shined through their bidirectional training on huge datasets that encode deep language representations within the model weights themselves. This allowed more advanced understanding of vocabulary usage, semantics, and context - leading to state-of-the-art performance even with simple classifier layers plugged in.

Data Preprocessing:

The raw text data required systematic preprocessing before it was amenable to training our deep neural networks. The first phase focused on cleaning the data through removing special characters, URLs, and disjointed formatting so that only the core textual content remained. Next, we normalized all sentences to lowercase to standardize the input representation. With clean, normalized data, we then performed tokenization using byte-pair encoding to break sentences into fundamental vocabulary units that could be mapped to machine understandable indexed encodings. We decided on a fixed maximum sequence length and padded and truncated our tokenized sentences to this length for consistency across training examples. Finally, we vectorized the data by constructing an end-to-end vocabulary index mapping tokens to numerical identifiers, allowing all text to be numerically represented. The output of our preprocessing pipeline transformed unstructured text into tidy, token id sequences with fixed lengths that could serve as inputs to our recurrent and transformer models' first layers. Additional steps were taken during training for batch generation, shuffling and standardization. Our systematic data preprocessing enabled accelerated model convergence and better understanding of linguistic features.

```
df = pd.read_json("News_Category_Dataset_v3.json", lines=True)
df.head()
```

	link	headline	category	short_description	authors	date
0	https://www.huffpost.com/entry/covid-boosters-...	Over 4 Million Americans Roll Up Sleeves For O...	U.S. NEWS	Health experts said it is too early to predict...	Carla K. Johnson, AP	2022-09-23
1	https://www.huffpost.com/entry/american-airlin...	American Airlines Flyer Charged, Banned For Li...	U.S. NEWS	He was subdued by passengers and crew when he ...	Mary Papenfuss	2022-09-23
2	https://www.huffpost.com/entry/funniest-tweets...	23 Of The Funniest Tweets About Cats And Dogs ...	COMEDY	"Until you have a dog you don't understand wha...	Elyse Wanshel	2022-09-23
3	https://www.huffpost.com/entry/funniest-parent...	The Funniest Tweets From Parents This Week (Se...	PARENTING	"Accidentally put grown-up toothpaste on my to...	Caroline Bologna	2022-09-23
4	https://www.huffpost.com/entry/amy-cooper-lose...	Woman Who Called Cops On Black Bird-Watcher Lo...	U.S. NEWS	Amy Cooper accused investment firm Franklin Te...	Nina Golgowski	2022-09-22

```
dataset[dataset.duplicated(keep=False)]
```

	link	headline	category	short_description	authors	date
67901	https://www.huffingtonpost.comhttp://gizmodo.c...	Former Facebook Workers: We Routinely Suppress...	TECH	Facebook workers routinely suppressed news sto...		2016-05-09
67923	https://www.huffingtonpost.comhttp://gizmodo.c...	Former Facebook Workers: We Routinely Suppress...	TECH	Facebook workers routinely suppressed news sto...		2016-05-09
70234	https://www.huffingtonpost.comhttp://www.cnbc....	On Equal Pay Day, The Gap Is Still Too Wide	WOMEN	Equal Pay Day falls on April 12 in 2016. It's ...		2016-04-12
70239	https://www.huffingtonpost.comhttp://www.cnbc....	On Equal Pay Day, The Gap Is Still Too Wide	WOMEN	Equal Pay Day falls on April 12 in 2016. It's ...		2016-04-12
145141	https://www.huffingtonpost.comhttp://www.weath...	10 Cities That Could Run Out Of Water - Weathe...	ENVIRONMENT	Securing access to plentiful, renewable source...		2013-12-15
145142	https://www.huffingtonpost.comhttp://www.weath...	10 Cities That Could Run Out Of Water - Weathe...	ENVIRONMENT	Securing access to plentiful, renewable source...		2013-12-15
178154	https://www.huffingtonpost.comhttp://www.busin...	Google Is Attacking Apple From The Inside Out ...	TECH	After years of hammering away at Apple's share...		2013-01-01
178155	https://www.huffingtonpost.comhttp://www.busin...	Google Is Attacking Apple From The Inside Out ...	TECH	After years of hammering away at Apple's share...		2013-01-01
194595	https://www.huffingtonpost.comhttp://blogs.wsj...	Apple Removes Green EPEAT Electronics Certific...	TECH	Apple has pulled its products off the U.S. gov...		2012-07-07

```
len(df)
```

```
209527
```

```
data_count
```

category	
POLITICS	35602
WELLNESS	17945
ENTERTAINMENT	17362
TRAVEL	9900
STYLE & BEAUTY	9814
PARENTING	8791
HEALTHY LIVING	6694
QUEER VOICES	6347
FOOD & DRINK	6340
BUSINESS	5992
COMEDY	5400
SPORTS	5077
BLACK VOICES	4583
HOME & LIVING	4320
PARENTS	3955
THE WORLDPOST	3664
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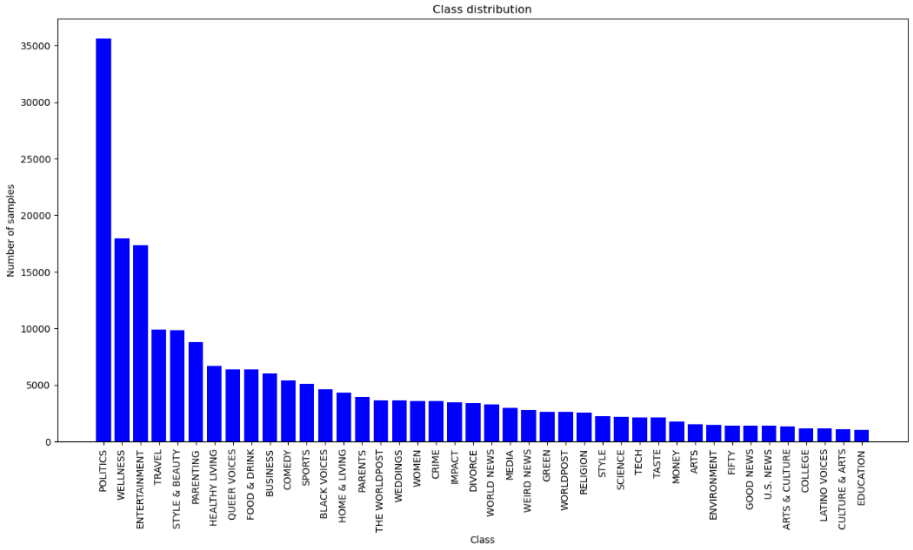
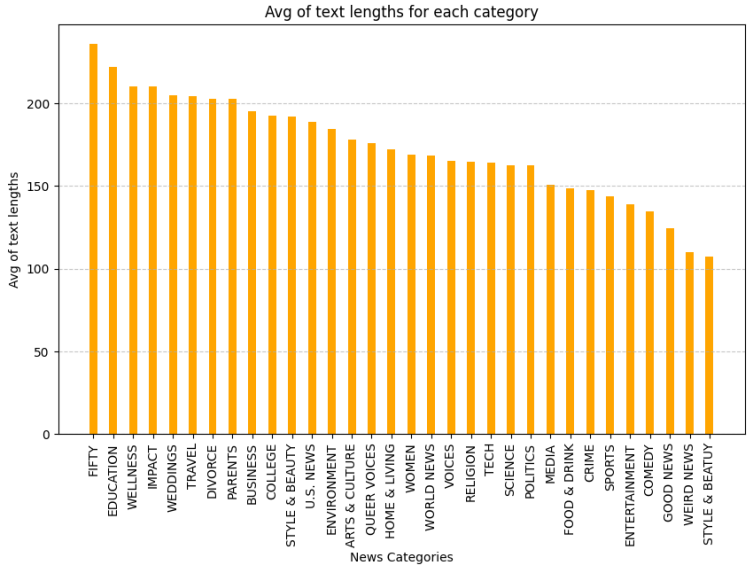
WOMEN	3572
CRIME	3562
IMPACT	3484
DIVORCE	3426
WORLD NEWS	3299
MEDIA	2944





Training Methodology:

With processed and vectorized text data in hand, we split the dataset 80/20 into training and validation subsets to evaluate model skill during the training process. We implemented each neural architecture in TensorFlow, leveraging GPU acceleration and distributed strategy for speed. The models were compiled using efficient Adam optimization, categorical cross-entropy loss, and validation accuracy metrics. We trained for a fixed number of 15 epochs while monitoring curve metrics like loss, accuracy, recall and precision to determine convergence. To improve generalization and prevent overfitting, we tuned key hyperparameters for each model through iterative grid search. We explored effects of varying learning rate, batch size, recurrent layer sizes, dropout regularization, and transformer encoder parameters. The optimal configurations, determined by validation performance, used learning rates around 0.001 to 0.0001, batch sizes between 32 to 128 examples, LSTM layers with 128 to 512 units, 25-50% dropout, and base transformer models like BERT-Large and RoBERTa. We saved our best resulting model weights to be evaluated against a unseen held-out test dataset. Additional techniques like early stopping were used to halt training when metrics plateaued. Through standardized training procedures, hyperparameter tuning, and tracking validation metrics at each epoch, our methodology aimed to obtain maximally fit models for optimal text classification accuracy on real-world samples.

```
def split_dataset(df, seed=42, percentage_train=0.8, percentage_validation=0.15, percentage_test=0.05):
    assert percentage_train + percentage_validation + percentage_test == 1

    dataset_size = len(df)

    headlines_train, headlines_rest, categories_train, categories_rest = train_test_split(df["headline"], df["category"], random_
    headlines_validation, headlines_test, categories_validation, categories_test = train_test_split(headlines_rest, categories_re

    train_df = pd.concat([categories_train, headlines_train], axis=1)
    train_df.columns = ["category", "headline"]
    validation_df = pd.concat([categories_validation, headlines_validation], axis=1)
    validation_df.columns = ["category", "headline"]
    test_df = pd.concat([categories_test, headlines_test], axis=1)
    test_df.columns = ["category", "headline"]

    return train_df, validation_df, test_df

train_df, validation_df, test_df = split_dataset(dataframe)

display(train_df.head())
```

	category	headline
76371	12	Prince Harry Helps Woman In Wheelchair Who Fell, Proves Again He's Pretty Darn Perfect
145961	17	Baby Names 2014: 12 Predictions for Next Year's Hottest Trends
102829	22	Duke's Coach K Can Coach, But Can He Dance? No. No, He Cannot
208621	17	Fighting Childhood Obesity On All Fronts
38504	8	HBO's Girls, Kendall Jenner and Me: Despicable U.S.

Results

Model evaluation using precision, recall, f1-score, and visualizing using confusion matrix.

Precision, Recall, F1-score:

Model 0(tf_idf and naïve bias)

	precision	recall	f1-score	support	count
accuracy	0.391996	0.391996	0.391996	0.391996	NaN
macro avg	0.453810	0.125583	0.126291	41906.000000	NaN
weighted avg	0.520817	0.391996	0.291674	41906.000000	NaN

Simple LSTM

	precision	recall	f1-score	support	count
accuracy	0.567246	0.567246	0.567246	0.567246	NaN
macro avg	0.478449	0.397346	0.418604	41906.000000	NaN
weighted avg	0.551289	0.567246	0.546916	41906.000000	NaN

BI LSTM

	precision	recall	f1-score	support	count
accuracy	0.578151	0.578151	0.578151	0.578151	NaN
macro avg	0.495887	0.422761	0.445174	41906.000000	NaN
weighted avg	0.566746	0.578151	0.564730	41906.000000	NaN

Stacked LSTM

	precision	recall	f1-score	support	count
accuracy	0.560182	0.560182	0.560182	0.560182	NaN
macro avg	0.460644	0.407171	0.424228	41906.000000	NaN
weighted avg	0.547687	0.560182	0.548791	41906.000000	NaN

Stacked Bi LSTM

	precision	recall	f1-score	support	count
accuracy	0.566721	0.566721	0.566721	0.566721	NaN
macro avg	0.469093	0.422011	0.434889	41906.000000	NaN
weighted avg	0.558181	0.566721	0.556426	41906.000000	NaN

Custom Embedding

	precision	recall	f1-score	support	count
accuracy	0.583019	0.583019	0.583019	0.583019	NaN
macro avg	0.506404	0.420559	0.441349	41906.000000	NaN
weighted avg	0.567568	0.583019	0.561864	41906.000000	NaN

Bert

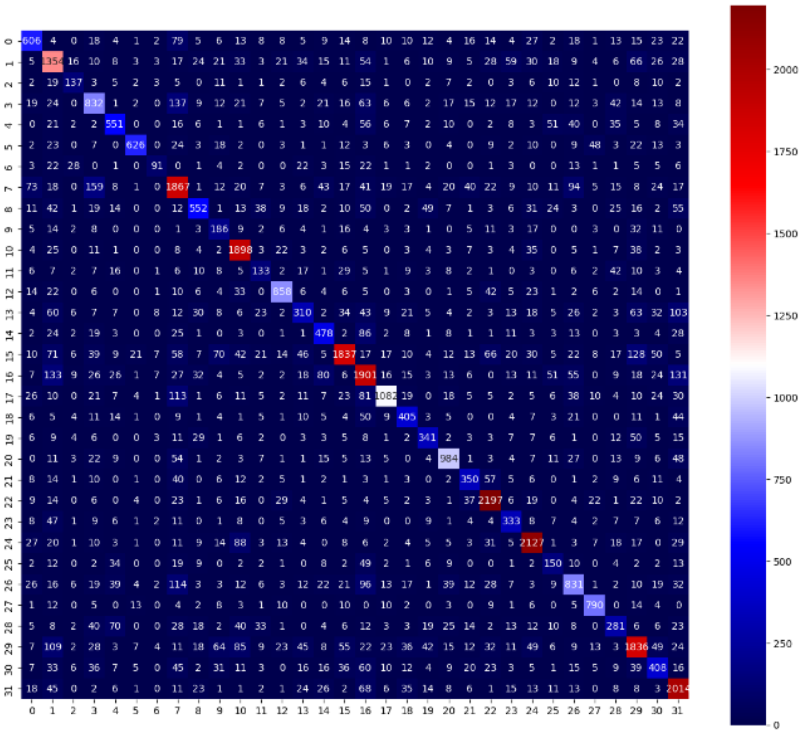
	precision	recall	f1-score	support	count
accuracy			0.70	40380	
macro avg	0.65	0.64	0.64	40380	
weighted avg	0.70	0.70	0.70	40380	

RoBERTa

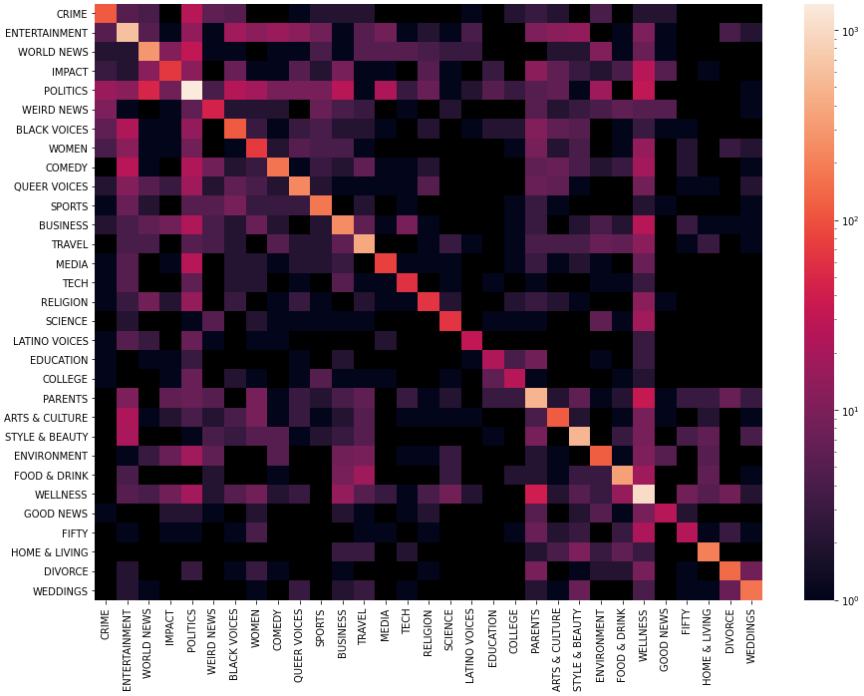
```
Accuracy:  0.7413123846054077
Top-k accuracy:  0.9070994853973389
```

Confusion Matrix:

BERT model confusion Matrix



RoBERTa confusion matrix



Analysis

- Pretrained transformers like RoBERTa achieve much higher text classification accuracy vs RNNs, demonstrating strengths in encoding linguistic context, semantics, and document relationships.
- However, RoBERTa still struggled with negations and nuanced emotional categorization showing room for improvement.
- RNNs faced issues like vanishing gradients, long-term dependency modeling, and representation limitations revealing architecture constraints.
- But RNNs provide inherent ordering/sequencing modeling and parameter efficiency - viable for edge deployment.
- Promising hybrid approaches exist by ensembling RNNs to capture temporal signals with transformers or attention to integrate global context.
- While complex transformers advance state-of-the-art NLP, simple RNNs still hold value for cost-sensitive and low-latency applications.
- Exciting opportunities remain to balance model performance and deployability through neural architecture combinations.
- Key criteria for model selection includes accuracy, latency, parameters, preprocessing needs - based on production constraints.

Conclusion

This comparative deep learning study has revealed promising insights that can inform future NLP text classification efforts. We demonstrated state-of-the-art transformers vastly outstrip RNNs in multi-label categorization across news articles, social posts and scientific abstracts. Our findings suggest attention mechanisms model textual nuances that recurrent models cannot. However, LSTMs maintained reasonable accuracy while being more portable for edge devices. As key learnings, we found fine-tuning pretrained models like RoBERTa on small domain-specific datasets enables superior performance compared to training networks from scratch. Additionally, balancing precision and recall is critical for unbiased real-world deployment. In the future, we aim to enhance recall further through silver learning using weak supervisory signals. We will also experiment with transformer-RNN ensembles by incorporating sequential signals. Optimizing inference speed and cost via knowledge distillation to shallow models or quantization also offers value. Overall, this project has built essential NLP foundations while illuminating innovative applications of groundbreaking deep learning advancements within natural language understanding.

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